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A neural network based approach for determination of optical scattering and absorption coefficients of biological tissue

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Abstract. The propagation of light in biological tissue depends on the absorption and reduced scattering coefficient. The aim of this project is the determination of these two optical properties using spatially resolved reflectance measurements. The sensor system consists of five laser sources at different wavelengths, an optical fibre probe and five photodiodes. For these kinds of measurements it has been shown that an often used solution of the diffusion equation can not be applied. Therefore a neural network is being developed to extract the needed optical properties out of the reflectance data. Data sets for the training, validation and testing process are provided by Monte Carlo Simulations. *Key words:* tissue optics, Monte Carlo, neural network.

1. Introduction

Biological tissues are considered as turbid media due to the scattering and absorption of light. The Propagation of light in a turbid medium can be described by the transport equation. Light interaction within the medium is influenced by three optical properties: absorption coefficient μ_a , the scattering coefficient μ_s and the scattering phase function. The later can be represented by the mean cosine scattering angle g that can be combined with the scattering coefficient to the reduced (or transport) scattering coefficient $\mu_s' = \mu_s(1 - g)$.

Various methods have been developed to determine the optical properties μ_a and μ_s' . In general all methods can be classified as transmission or reflectance measurements. Moreover methods can be invasive, minimal invasive or non-invasive. The evaluation can either be based on constant light measurements, time resolved measurements or modulated light measurements. This work uses constant light and spatially resolved reflectance data provided by a non-invasive fibre probe.

2. Theory

The propagation of radiation in turbid media depends on the properties of the medium. The scattering coefficient μ_s and anisotropy parameter g , that describes the average of the scattering angle, are combined in the reduced or transport scattering coefficient μ_s' . Moreover the absorption coefficient μ_a and the refractive index n are required for appropriate interpretation. In the wavelength band of 600 – 1300 nm the coefficients for soft tissues are approximately $0.1 - 10 \text{ cm}^{-1}$ for μ_a and $100 - 1000 \text{ cm}^{-1}$ for μ_s ¹. Typical values for anisotropy parameter g are between 0.8 and 0.95 for most tissues². Bolin *et al.*³

measured the refractive index for various mammalian tissues at 630 nm. The reported values for soft tissue are between 1.38 and 1.41. He also reported a slightly decrease of refractive index with increasing wavelength. There are further two optical properties that contain the remaining properties μ_a and μ_s . These are the effective attenuation coefficient μ_{eff} and the optical transport coefficient μ'_t .

$$\mu'_t = \mu_a + \mu'_s \quad (1)$$

$$\mu_{eff} = \sqrt{3 \cdot \mu_a \cdot \mu'_t} \quad (2)$$

For measuring backscattered light, the geometry of the fibre probe is of utmost importance. The penetration depth depends on the source-detector separation. Leahy⁴ demonstrated using a series of human oxygen de-saturation experiments that the optimal source-detector separation for reflection pulse oximetry using 675 nm and 790 nm sources on human tissue is approximately 5 mm. Kumar *et al.*⁵ also reported that the optimal source-detector separation of between 2 mm and 5 mm is appropriate for near infrared spectroscopy (800 – 2500 nm).

To create neural networks, different data sets within the known range of optical properties have to be created. For this process a Monte Carlo Simulation has been adapted in Matlab. The principle of Monte Carlo simulations and its stochastic simulation of the “random-walk” of photons has been described in literature⁶. For all simulations the tissue was assumed to be semi-infinite, with an index of refraction n of 1.4 and an anisotropy factor g of 0.875.

3. Materials and Methods

The hardware setup consist of laser diodes with different wavelengths in the range of 685 to 905 nm, five photo diodes, each for one source detector separation and an optical fibre probe. The optical fibre probe was created regarding to the specifications mentioned above. Figure 1 shows the tip of the probe, with its five source fibres in the middle and with four detection fibres for each of the five source-detector separations.

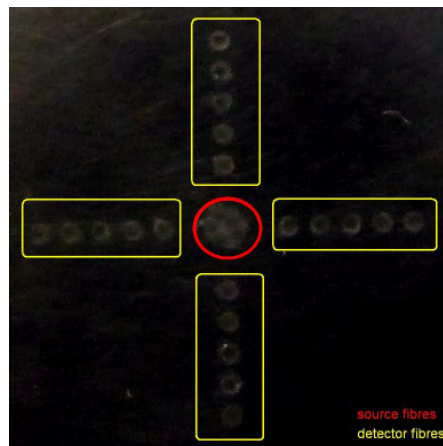


Figure 1: fibre sensor tip with input fibres in the middle and surrounding detector fibres

The five chosen source-detector separations are 2, 3, 4, 5 and 6 mm. The reflectances at those separations were simulated by Monte Carlo simulations for different combinations of optical properties. The next process step is the creation of a neural network based on the created data sets. For every combination of optical properties one million photons were traced. This is necessary to get an

accurate spatially resolution. The range of optical properties that were used to create the data sets were 0.02 to 1 mm⁻¹ for μ_a and 0.6 to 2.5 mm⁻¹ for μ_s' . Three data sets were created. The training data set comprises 2300 different combination of optical properties. The whole training data set was created with a given step size in optical properties. For the validation and testing process data sets with 1000 randomized optical properties were created. Different neural networks were trained with the created data sets. The parameters that can be changed are the transfer functions between the nodes of each layer, the number of hidden layers, the number of nodes for each layer and the output parameters.

Regarding the number of hidden layers it turned out that more than three hidden layers will not improve accuracy but computation time. This is valid for the number of nodes too. Also important are the type of transfer function between each layer and the training algorithm. First computation results showed that the lowest RMS errors are given by applying the hyperbolic tangent sigmoid transfer function and the Levenberg-Marquardt training algorithm. Comparing the trained networks using μ_a , μ_s' and μ_{eff} , and μ_t as outputs it turned out, that the second mentioned pair of optical properties lead to more accurate results. After determining μ_{eff} and μ_t , μ_a and μ_s' can be extracted.

4. Results and Discussion

Figure 2 displays the optical properties that were calculated by the neural network versus the simulated ones. The results of the first trained networks showed RMS errors of approximately 19% for μ_{eff} and 11% for μ_t . The resulting RMS errors for μ_a and μ_s' are 28% and 9%, respectively. This discrepancy has been approved in literature⁷.

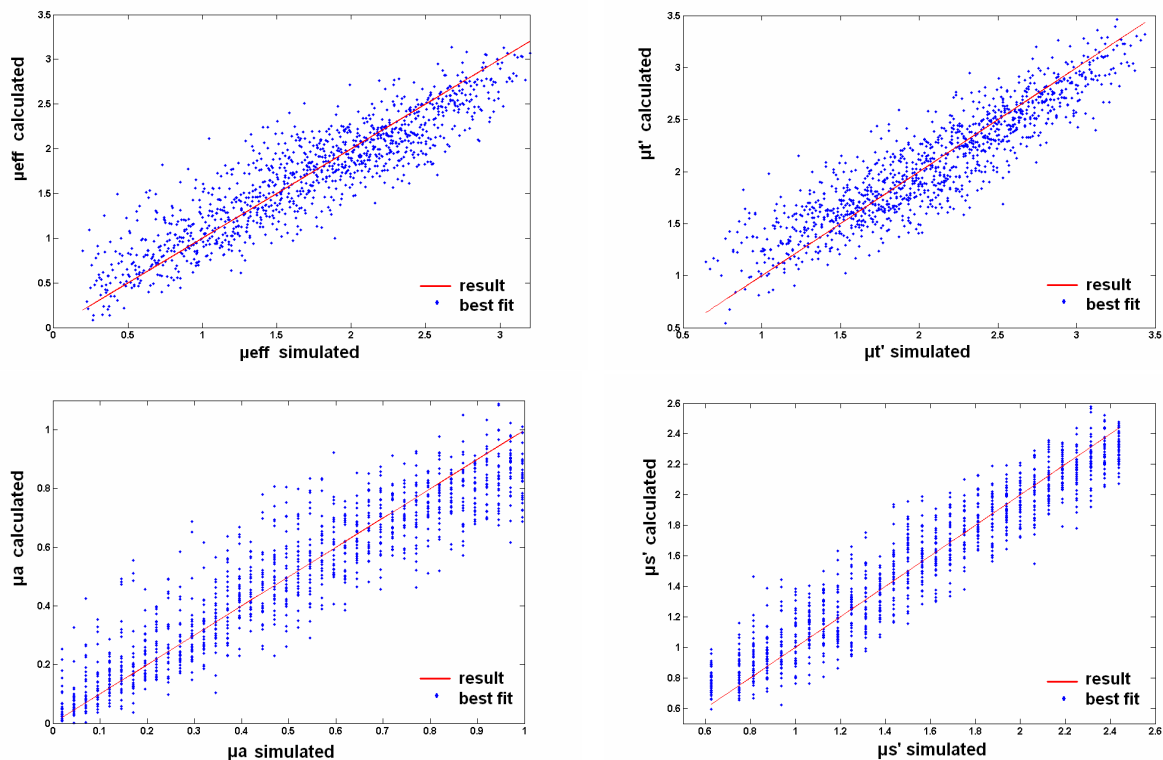


Figure 2: simulated versus estimated values of μ_{eff} (top left), μ_t' (top right), μ_a (bottom left) and μ_s' (bottom right)

The first trained networks showed promising results, which are not yet applicable. The error demands further investigation to optimize the performance of the neural network and to reduce the resulting errors. There are two possible error sources. The reflectance data of the Monte Carlo simulation could be a too imprecise, which is a result of an unnecessary photon count. Another fact could be the layout of the neural network itself. To test the accuracy of the Monte Carlo simulations, several runs with different number of photon counts were started. The results of the simulation are shown in Figure 3.

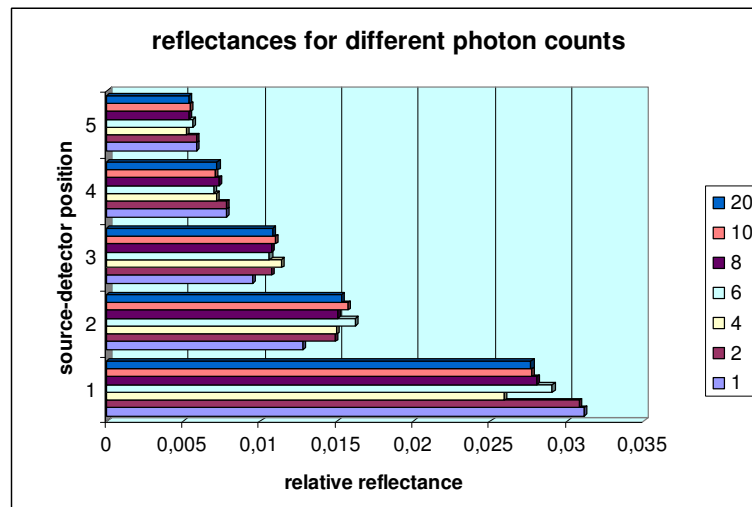


Figure 3: dependency of reflectance on photon count

The legend shows the photon count in the range of 1 million to 20 million photons. The results clarify the assumption of inaccurate simulation results. Especially for simulations that were started with less than 10 million photons.

5. Conclusions

Results of the first trained neural networks showed promising results, which are not yet applicable for this project. As shown above, new data sets have to be created with a higher photon count of approximately 10 million photons. This is a very time consuming task in the order of days and weeks. Moreover the neural network itself needs some more testing to achieve further decrease in the resulting error. For determination of optical properties using neural networks based on diffuse reflectance measurements Kienle *et al.*⁷ showed that RMS errors of 14% and 3% are possible for μ_a and μ_s' , respectively. With an accurate neural network the next project step can be initiated. This next step is the fusion of the neural network with the fibre probe assembly.

6. Acknowledgements

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